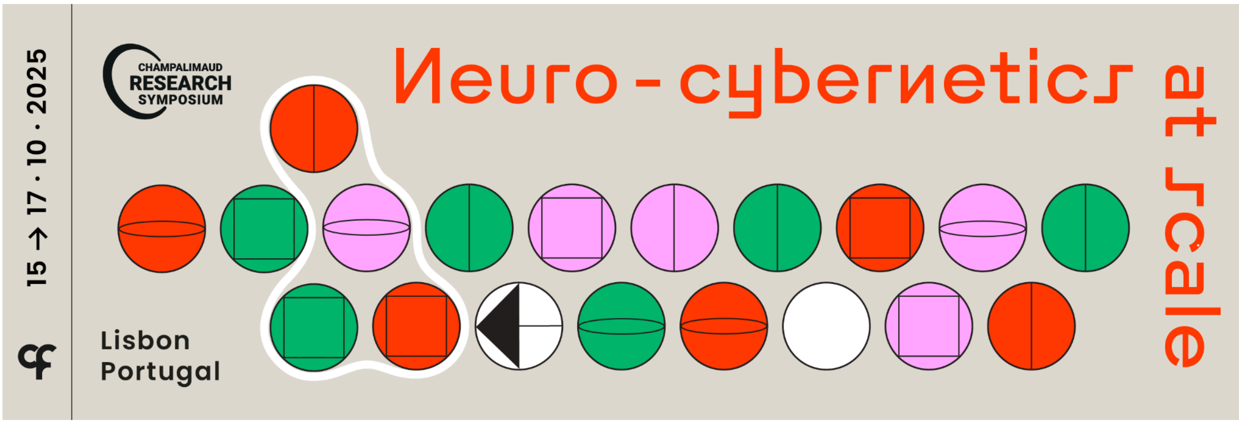

A Unified Perspective on Computation and Stochastic Spiking Neural Activity

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Current models of neuronal computation cannot account for the nature of the irregular spike trains observed in the cortex. While being good at implementing computationally useful low-dimensional dynamical systems [1,2], the link of current RNN models with real neural dynamics is not well understood [3].

Meanwhile, classical models of irregular desynchronized neocortical activity based on balanced excitation and inhibition, are not designed to implement the general and flexible dynamics neural systems should produce to drive behavior and cognition, despite being able to explain the irregular nature of spike trains and predict most cortical activity statistics [4-6].

Here we present a mathematical model of a spiking neural network that is capable of codifying distributed latent variables while maintaining E-I balance, bridging the advantages of both of the previous paradigms.

A mean-field analysis reveals that the combination of these two architectures entails novel dynamical features that are not present in either of the previous models. We show that, when activity in the latent subspace evolves in time, maintaining balance requires coherent fluctuations in average membrane potential across the neurons, and also nontrivial dynamics in the distribution of firing rates, which coexist with constant and decorrelated activity at the level of the global activity of the network. These counterintuitive results provide novel predictions which we are currently trying to test.

In terms of neural tuning curves, in contrast to current low-rank models – whose units generate monotonous and symmetric mixed responses – our network shows more complex kinds of nonlinear mixed selectivity, closer to those observed [7,8].

Our results provide a long-sought bridge between bottom up and top down views of computation as instantiated through the dynamics of recurrent neural circuits.

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